How Do People with Limited Movement Personalize Upper-Body Gestures? Considerations for the Design of Personalized and Accessible Gesture Interfaces

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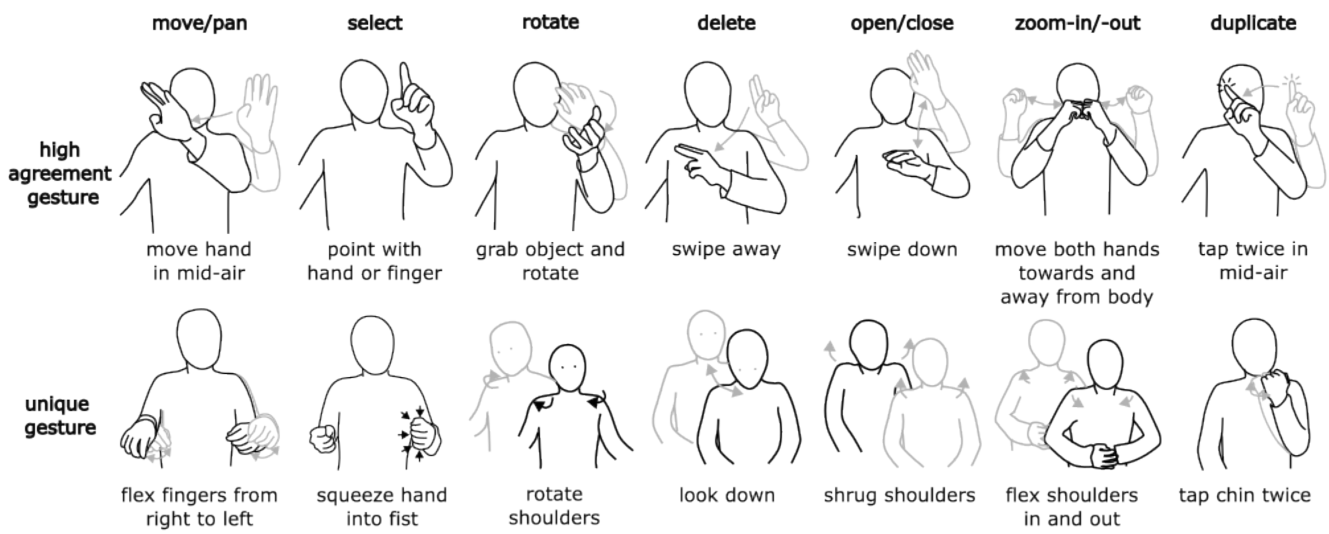

Figure 1: ***Personalized upper-body gestures authored by 25 participants with upper-body motor impairments.*** **The top row represents gestures that multiple people designed and the bottom row represents a unique gesture that only one participant came up with. Some of our participants designed gestures where they solely activated their muscles but did not visibly move (e.g., *select,* unique gesture) or gestures that used shoulder (e.g., *delete,* unique gesture) or head (e.g., *zoom-in/-out,* unique gesture) movement.**

Abstract

Always-on, upper-body input from sensors like accelerometers, infrared cameras, and electromyography hold promise to enable accessible gesture input for people with upper-body motor impairments. When these sensors are distributed across the person's body, they can enable the use of varied body parts and gestures for device interaction. Personalized upper-body gestures that enable input from diverse body parts including the head, neck, shoulders, arms, hands and fingers and match the abilities of each user, could be useful for ensuring that gesture systems are accessible. In this work, we characterize the personalized gesture sets designed by 25 participants with upper-body motor impairments and develop design recommendations for upper-body personalized gesture interfaces. We found that the personalized gesture sets that participants designed were highly ability-specific. Even within a specific type of disability, there were significant differences in what muscles participants used to perform upper-body gestures, with some predominantly using shoulder and upper-arm muscles, and others solely using

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their finger muscles. Eight percent of gestures that participants designed were with their head, neck, and shoulders, rather than their hands and fingers, demonstrating the importance of tracking the whole upper-body. To combat fatigue, participants performed 51% of gestures with their hands resting on or barely coming off of their armrest, highlighting the importance of using sensing mechanisms that are agnostic to the location and orientation of the body. Lastly, participants activated their muscles but did not visibly move during 10% of the gestures, demonstrating the need for using sensors that can sense muscle activations without movement. Both inertial measurement unit (IMU) and electromyography (EMG) wearable sensors proved to be promising sensors to differentiate between personalized gestures. Personalized upper-body gesture interfaces that take advantage of each person's abilities are critical for enabling accessible upper-body gestures for people with upper-body motor impairments.

CCS Concepts

• **Human-centered computing → Empirical studies in accessibility**; **Gestural input**.

Keywords

accessibility, motor impairments, gestures, input

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1 Introduction

Device interactions are rapidly shifting from intermittent finger input using interfaces like touchscreens, keyboards, or mice to always-on, upper-body input from sensors like accelerometers [33, 59], infrared cameras [42], and electromyography [15, 27] sensors. When these sensors are distributed across the person's body, they can sense and interpret gestures not just from the user's fingers, but also movement from their arms, shoulders, and neck. As these upper-body sensors become increasingly ubiquitous, they can enable accessible, comfortable input for people with upper-body motor impairments because people can use various body parts and gestures for device interaction. We are just beginning to see upper-body gestures being incorporated into technologies like virtual or augmented reality. However, many of these gesture systems today are primarily designed for people without disabilities. They use a specific, fixed gesture set that usually assumes precise control over the fingers and arms and the ability to hover the hand in mid-air (i.e., perform mid-air gestures). In contrast, the abilities of people with upper-body motor impairments can vary significantly between people and over time [34]—some people may be able to do standardized gestures but experience rapid fatigue, while others may experience significant difficulty moving their fingers and arms. Due to this diversity in abilities, *personalized upper-body gestures* that enable input from various body parts, according to the abilities of each user, could be useful for ensuring that gesture systems are accessible [22, 68]. However, we do not know what types of gestures (or gesture sets) people with upper-body motor impairments would want to use, or whether wearable sensors can differentiate between an individual's chosen gestures. To answer these and related questions, we conducted a study capturing upper-body gestures (i.e., movements that involve the head, neck, shoulders, arms, hands and fingers but not facial gestures) designed by 25 participants. We characterize the personalized gesture sets our participants created and use these to develop design recommendations for personalized gestures for people with upper-body motor impairments.

Personalization is key to ensuring that interfaces are accessible for users with heterogenous and diverse abilities [22, 23, 67, 68]. Prior work has looked at how personalized algorithms can improve touchscreen [44] and mouse [66] input, as well as input from wearables such as smartwatches [35], head-mounted displays [36], and wheelchairs [7] for users with upper-body motor impairments. These works primarily explore how accessibility of one- or two-dimensional input with switches or touchscreens can be improved with inclusive algorithms [44] or more accessible touchscreen placement [36], but not input that encompasses the entire upper-body. Additionally, participants who have a high degree of disability (e.g., cannot move or control arms or fingers) are usually excluded from these studies, as they require some amount of movement to interact with touchscreens. Our work expands on this by exploring how people with various levels of upper-body motor impairments, including those who have no movement below their neck and shoulders, perform upper-body gestures for commonly used device functions (e.g., *zoom-in, select, open*).

One of the goals of this work was to understand what types of sensor technologies could be used for personalized upper-body gesture recognition, towards the goal of designing and implementing working gesture recognition systems. While eye tracking is becoming more common, such sensors are only viable for specific use cases (such as while using an augmented or virtual reality headset) or too conspicuous for use in public. Therefore, we focused on a complementary approach, EMG and IMU sensors. These are wearable sensors that can recognize gestures, can be used discreetly in public, and are useful for interaction with a range of applications and operating systems.

To elicit personalized gestures, we leverage prior work on developing user-defined gestures for devices like interactive tabletops [69], smartphones [51], and virtual or augmented reality [48]. Most user-defined gesture studies focus on developing a unified gesture set with unimpaired participants for a set of functions that are needed to interact with a device [60, 61]. Adopting terminology from prior work, we define a *gesture* as a movement or action that is meant to bring about a result. A *function* is the result of a gesture or a task that the person wants to accomplish. For example, a person could swipe horizontally across the screen (a gesture) to answer a phone call (a function). Such gesture sets are usually inaccessible for people with upper-body disabilities [1, 59], as they do not take into account each users' unique abilities [44]. Significantly limiting the body part that participants can use to perform the gesture, such as above the neck [57, 75] or solely the eyelids [16] can result in an accessible unified gesture set that are intuitive to both participants with and without motor impairments. However, constraining the gestures to solely above the neck does not take advantage of the full range of abilities that the user has.

Additionally, to design an accessible gesture interface, the personalized gestures must be differentiable from each other using upper-body sensors. Inertial measurement unit (IMU) sensors and electromyography (EMG) sensors are two wearable sensors that hold promise for enabling upper-body input. IMU sensors are already integrated into many mobile and wearable devices like smartphones and smartwatches. Although EMG sensors have not yet been widely implemented and adopted, these sensors hold promise for enabling always-on and unobtrusive device input [52]. We compared how differentiable the gestures are between and within personalized gestures designed for specific functions for IMU and EMG sensors.

In this work, we characterize upper-body personalized gesture sets created by individuals with upper-motor disabilities. We asked 25 participants to design personalized gestures for 10 common device functions (e.g., *zoom-in, select, open*). To help quantitatively characterize participants' gestures and determine whether personalized gestures can be differentiated from each other, we distributed combined IMU and EMG sensors across the participants' upper-body, including their neck, shoulders, upper-arm, forearms, and fingers. Our goal is to understand how we can build interfaces that support personalized upper-body gestures for people with upper-body motor impairments. To this end, the main contributions of our paper include:

- An analysis of the personalized gestures that 25 participants with upper-body motor impairments designed for 10 functions (e.g., *zoom-in, select*), including participants' motivations for designing specific gestures and quantifying similarities and differences between each participant's personalized gesture sets.
- An analysis of personalized gesture properties and how they impact ability assumptions potentially underlying currently available upper-body gesture interfaces, and design recommendations to enable more accessible upper-body gesture interfaces.
- A quantitative analysis of how differentiable two wearable sensor (IMU and EMG) signals are within and between personalized gestures and recommendations for future gesture recognition systems.

Our results suggest that gestures are highly personalized between participants and the choice in how they perform the gestures are ability-dependent. We identified three gesture properties (1) body part used, 2) arm location relative to rest of body, 3) dynamic gesture choice) that may not fit with ability assumptions potentially underlying currently available upper-body gesture recognition systems. Therefore, we present three design considerations: 1) track the whole upper-body, 2) use sensing mechanisms that are agnostic to the location and orientation of the body, and 3) use sensors that can sense muscle activations without movement, for designing accessible upper-body gesture interfaces. Wearable sensors like IMU and EMG sensors have high differentiability between each personalized gesture and hold promise to enable accessible upper-body device interactions for users with upper-body motor impairments.

2 Related Work

Our work expands on prior research in personalized input for users with and without disabilities by extending to upper-body gesture input. To elicit gestures from our participants, we draw from methods formalized in user-defined gestures studies [65, 69]. We highlight the benefits and drawbacks of different sensors that can be used for upper-body gesture recognition. Lastly, we discuss prior work on upper-body gestures primarily in augmented and virtual reality, and highlight ability assumptions [67] that may make it challenging to extend such work to users with upper-body motor impairments.

2.1 Personalized Input

Personalized interfaces that dynamically adapt to each user's abilities and *"reflect each person's unique abilities, devices, and environment"* [22] can enable more effective and accessible device interaction. For example, personalized touchscreen [44] and mouse [66] input significantly improved touch and pointing performance for people with upper-body motor impairments. Personalization also improves device interactions for people without disabilities. For example, personalized keyboard layouts improved typing speed [20] and accuracy [21], and personalized gesture sets are easier to remember than expert-designed gesture sets [45].

However, prior work investigating the accessibility of emerging wearable devices for people with upper-body motor impairments remains sparse [56]. Malu et al. explore how smartwatches [35] and head-mounted displays [36] could be made more accessible with personalized touch-based smartwatch gestures and adjustable wearable touchpads. Additionally, Carrington et al. [7, 8] explore how chairables (i.e., wearables that are specifically designed to work within the space of a wheelchair) can improve mobile device accessibility by personalizing the location of switches, touchpads, and force sensors on a wheelchair arm. However, most prior work in personalized gesture elicitation focuses on personalizing touch-based one- (e.g., switches) or two- (e.g., touchscreen) dimensional input using the person's fingers or hand, which often limits the potential participant pool to participants who have some motion in their hands and fingers, excluding participants who cannot move those body parts. Additionally, limiting interactions to the hands and fingers does not take advantage of the users' full abilities [67].

Lastly, personalized gesture recognizers have been explored extensively for 2-dimensional gestures (i.e., on a touchscreen), mostly for unimpaired users. The $-family recognizers [70] have had significant impact in enabling low-cost and easy-to-use gesture recognition. Algorithms that can identify upper-body user-specific gestures are beginning to emerge for unimpaired users. Xu et al. [73] implemented a few-shot learning framework that enabled users without motor impairments to add personalized gestures when using a smartwatch. Wang et al. [63] enabled personalized gesture authoring in augmented reality. However, many of these studies do not include participants with upper-body motor impairments, and it is not clear whether currently available sensor technologies like smartwatches [73] or camera-based sensors [63] can sufficiently capture the diversity of personalized gestures that users with disabilities may come up with. For example, a sensor placed on the wrist may not be able to sense head, neck, or shoulder movement, and a camera-based sensor may not be able to sense muscle activation without movement.

2.2 User-Defined Gestures

Gesture elicitation [65, 69] as a design method is an alternative to designing gestures by professionals. Gesture elicitation has been shown to be a useful tool to design gestures that are conceptually simple and preferred by end-users for a variety of applications [43, 60]. Much of the prior work in user-defined gestures focused on creating one cohesive gesture set for all users that is easy to remember and perform that have high agreement among participants [60–62, 69]. The protocol for eliciting user-defined gestures has been used to developed gesture sets for interactive tabletops [45, 69], smartphones [51], smart homes [31], and virtual or augmented reality [48], among others. The general methodology for such studies is to first determine a set of desired *functions* for a specific interactive device or system, prompt and elicit gestures from participants to perform those functions, and then come up with a cohesive gesture set where gestures do not conflict between different functions. *Functions* are tasks that users may want to accomplish on a device—for personal computing devices like a smartphone or computer, a function might be *zoom-in* or *select* [69]. For a smart home, a function might be *turn on lamp* or *shut the blinds* [31]. A *gesture*, on the other hand, is the movement or action (e.g., swipe hand down) that results in the desired function. Multiple gestures can be mapped to a single function if so desired.

The application of this methodology to users with disabilities has been, to date, quite limited. Kane et al. [29] compared blind and sighted user-defined gestures on a touchscreen and found that blind participants relied on keyboard metaphors more heavily than sighted participants. Dim and Ren [14] developed a gesture set that enabled blind people to access smartphone features by tilting their phones. Zhao et al. [75] investigated above-the-neck (e.g., mouth, head, eyes) user-defined gestures with people with upper-body motor impairments for smartphone use, finding that participant-chosen gestures focused on eye movements that were simple, easy to remember, and less likely to draw attention from others. Fan et al. [16] demonstrated that eyelid gestures are feasible for interacting with mobile devices. Building on these studies, our work aims to characterize how people with upper-body motor impairments design upper-body gestures using their fingers, arms, shoulders, and neck. A key difference between the prior studies and our study is that we focus on characterizing the personalized gestures that participants design, rather than developing a unified gesture set. We did this because we anticipated that our participants will have low gestural overlap due to great differences in their physical abilities.

When looking more broadly at mid-air gestures in general, there has been extensive prior work looking at how mid-air gestures can improve health [24, 25] and accessibility [3, 6, 17, 18] for older adults with and without disabilities. Gerling et. al [24, 25] and Bobeth et al. [3] demonstrated that older adults find mid-air gesture games and interactions enjoyable and encourage movement. Ferron et. al [17, 18] and Carreira et al. [6] demonstrated that older adults generally found mid-air gestures comfortable to do, but there was a large variability in how people performed the gestures. These studies focused on testing people's preferences on standardized mid-air gesture sets, rather than on personalized gesture sets as we do in this study.

2.3 Sensors for Upper-Body Gesture Recognition

Sensors that hold promise towards enabling upper-body input include inertial measurement unit (IMU) sensors, camera-based sensors, and electromyography (EMG) sensors. We are interested in understanding whether such sensors distributed across a person's upper body could improve upper-body gesture accessibility for people with upper-body motor impairments. IMU sensors are integrated into many mobile and wearable devices like smartphones and smartwatches. IMUs sense linear and rotational acceleration with accelerometers and gyroscopes, respectively. While one IMU sensor on the wrist might not provide sufficient information for upper-body control, IMU sensors distributed across the body can be used to perform human motion tracking [49].

Similar to IMU sensors, infrared cameras like the Microsoft Kinect [41] can perform human motion tracking by extracting changes in pose using computer vision [9]. Although motion tracking with depth cameras can be less invasive and easier to set up than wearable sensors, depth cameras suffer from changes in the environment such as lighting [4].

Lastly, EMG sensors sense muscle electrical activity generated when a person moves or flexes their muscles [12, 74]. Similar to IMU sensors, they can be placed solely on the wrist or upper arm [38], or be distributed across the body, which may provide more information for upper-body gestures. While EMG sensors have not yet been widely implemented and adopted, these sensors hold promise for enabling always-on and unobtrusive device input [52]. EMG sensors can be used to sense user input even when the user is flexing but not moving their arm by placing the sensors over the muscle belly. Sensor fusion [28] is one way in which the benefits and drawbacks of these gesture-sensing systems can be leveraged depending on the user's abilities. Another option is to choose different sensor modalities based on the user's abilities [53]. For our work, we are primarily interested in understanding how wearable interfaces could improve upper-body gesture accessibility, as wearable sensors provide always-on input. Therefore, we include preliminary comparisons to quantify whether IMU and EMG sensors can differentiate between personalized gestures.

2.4 Assumptions Underlying Currently Available Upper-Body Gesture Sets

We briefly summarize some ability assumptions [67] underlying currently available upper-body gesture sets. It is important to determine how sensor choice could affect the accessibility of these gesture interfaces. Currently available upper-body gesture sets often have ability assumptions embedded in them that could make the gestures inaccessible for users with upper-body motor impairments [61]. For examples, gestures that require precise control over finger, hand, and arm movements or require gestures to be performed with a specific hand would not be accessible to someone with difficulty controlling their arm movements or who have limb differences. One major ability assumption embedded in many of the proposed gesture sets is that many of the proposed upper-body gesture sets are mid-air gestures, where the user raises one or two hands to chest-level to virtually interact with an interactive device [61]. The assumption that users can perform mid-air gestures was embedded in many applications including smart homes [58], wall displays [64] and augmented or virtual reality [71]. Mid-air gestures are also currently the standard for interacting with commercially available technology like smartwatches [2] and augmented [40] and virtual [39] reality devices.

Even if users with upper-body motor impairments could perform gestures involving precise finger, arm, or shoulder movements, the assumption that the person is performing gestures in mid-air versus while resting their arm on an armchair or at hip-level could pose a challenge for existing approaches to gesture recognition. Many mid-air gesture recognizers use camera-based technologies that extract and use arm joint angles relative to the rest of the body to detect gestures [5, 50]. Other gesture recognizers use radio frequency to extract point cloud information about the location of the person's hand relative to their body to differentiate between gestures [32, 47] In such scenarios, even if the person is moving their hand and fingers through the motions of the standardized gestures, the algorithm may have a difficult time recognizing gestures that are not performed in mid-air at chest-level. In such scenarios, sensors that are agnostic to the location of the hand relative to the rest of the body, such as the aforementioned IMU and EMG sensors, may enable improved recognition of standardized gestures regardless of where the gesture is being performed. Our work aims to understand whether our participants' abilities fit the ability assumptions underlying currently available standardized upper-body gesture sets and to develop design considerations for inclusive upper-body gesture recognition.

3 Method

The goal of this study was to characterize personalized gestures for people with upper-body motor impairments for 10 common device functions (e.g., *zoom-in, open, delete*). We placed IMU and EMG sensors on the participants' upper-body to quantitatively characterize the gestures. The protocol was approved by the University of Washington, Seattle's Institutional Review Board (IRB #STUDY00016152) and all participants consented to the study.

3.1 Participant Characteristics Summary

We recruited participants from the greater Seattle community by distributing flyers to relevant community listservs. We recruited participants who are able to move their head from side to side because we wanted to focus on upper-body gestures rather than eye-based gestures, which has been investigated in prior studies [16, 75].

Our 25 participants had various disabilities that affected their ability to physically interact with technology, including spinal-cord injury (13), muscular dystrophy (3), peripheral neuropathy (3), essential tremor (2) and other disability (4). Twelve participants identified as men, eleven identified as women, and two identified as non-binary. The participants' races included[1] Caucasian/white (23), Black (2), and Asian (1). Nineteen participants were right-handed, two were left-handed, and four were originally right-handed, but switched to being left-handed after disability onset.

The average age and standard deviation of our participants was 49 years ± 18, with the youngest participant being 22 and the oldest participant being 77. Participants had a wide range in the number of years since their disability onset, with an average of 17 years ± 16. The minimum years since their disability started affecting their ability to interact with technology was 2, and the maximum was 68 years. The age at which they experienced the onset of their disability affecting their ability to interact with technology was 32 years ± 19, with some being affected since birth, and others experiencing disability onset at age 68. All but one of our participants had prior smartphone experience. Some used touchscreen gestures to use their smartphones, while others used accessibility tools such as voice-to-text to interact with their smartphones.

We had a range of DASH (Disabilities of Arm, Shoulder and Hand) scores, which is a qualitative measure of disability and its effect on the person's daily life, with higher scores correlating to greater effects on life. The average DASH score was 58 ± 18, with a minimum DASH score of 14 (i.e., disability has a minor effect on their daily lives) and a maximum DASH score of 82 (i.e., disability has a significant affect on daily life).

3.2 Sensor Placement and Apparatus

We placed 16 dry electrodes on the participants' left and right shoulders, upper-arm, forearm, and finger muscles according to Cram's [11] and SENIAM [26] guidelines (Fig. 2). We used Delsys Trigno Avanti sensors (Delsys Inc, Boston, MA, USA) for the shoulder and upper-arm muscles and Delsys Trigno Duo sensors (Delsys Inc, Boston, MA, USA) for the forearm and finger muscles. We obtained IMU signals from the Delsys Trigno Avanti sensors placed on the person's shoulders and upper-arm muscles and the Delsys Trigno Duo Sensor body placed on the person's forearm and wrist.

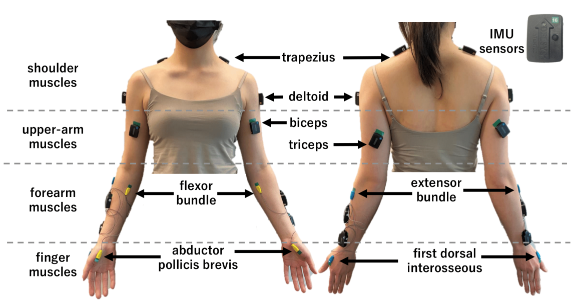

Figure 2: *IMU and EMG Sensor Placement.* IMU sensors were placed on the participant's shoulders, upper-arms, forearms, and wrist (i.e., the large black sensors). The large black sensors on the person's forearm and wrist only sense IMU signals. EMG sensors were placed on the participant's shoulders (trapezius: `trap` and deltoid: `delt` muscles), upper-arms (biceps: `bic` and triceps: `tri` muscles), forearms (extensor: `ext` and flexor: `flex` bundles), and fingers (abductor pollicis brevis: `APB` and first dorsal interosseous: `FDI` muscles). The small yellow and blue sensors only sense EMG signals. The placements were chosen to sense movement or muscle activation from the person's upper-body, including the fingers, arms, shoulders, neck, and head.

[1]Some participants identified with multiple races

We developed the main data collection software on Unity (`ver2021.3.13f1`). The Avanti sensors collected EMG data at 1259 Hz and IMU data at 148 Hz. The Duo sensors collected EMG data at 1926 Hz and IMU data at 74 Hz. We used the Delsys software development kit to integrate our data collection with Unity. The software development kit synchronized the IMU and EMG sensor data and upsampled all EMG signals to 2000 Hz and IMU signals to $148.1\bar{4}8$ Hz. After sensor placement, we assessed each sensor for signal quality to ensure that each sensor was placed over the muscle belly of the intended muscle. These sensors are traditionally used in clinical settings to diagnose and assess treatment outcomes [55]. Sensors of this fidelity in this many locations are most likely not essential for differentiating between personalized gestures. For this study, we chose to use high-fidelity sensors to ensure that we can accurately characterize how differentiable gestures are in the best case scenario and quantify which muscles participants activated to perform their gestures.

3.3 Procedure

We first asked participants to fill out a short demographics questionnaire that asked about their disability, age, and gender and how their disability affects their ability to interact with technology. Our goal was to collect data from a diverse set of participants, as the person's cultural background can affect the types of gestures they come up with [72]. We also asked questions from the QuickDASH [30] (Disabilities of the Arm, Shoulder, and Hand). The QuickDASH is a qualitative measure of the extent to which the person's disability that affects their arm, shoulder, or hand affects their activities of daily living. We modified the questions slightly to alleviate ableist assumptions that the person's disability that affects their arm, shoulder, or hand is a <u>problem</u>. For example, one question asks "...to what extent has your arm, shoulder or hand <u>problem</u> interfered with your normal social activities...?". This was replaced by "...to what extent has your arm, shoulder or hand <u>affected by your disability and/or chronic condition</u> interfered with your normal social activities...?"

We then asked participants to come up with gestures for 10 functions originally proposed in Wobbrock et al. [69]: 1) *move*; 2) *select*; 3) *rotate*; 4) *delete*; 5) *pan*; 6) *close*; 7) *zoom-in*; 8) *zoom-out*; 9) *open*; 10) *duplicate*. We chose to prompt participants with the 10 functions above because they have low conceptual complexity in Wobbrock et al. [69]. Each function was presented to the participant with both video and voice command using simple objects (square, triangle, circle) rather than a specific application to ensure that the participants were not being influenced by a specific device type (e.g, tablet, computer, smartphone). For example, for *zoom-in*, we showed our participants a video of a group of objects (a square, triangle, and circle) expanding in size with the voice over: *"Zoom-in. Pretend you are adjusting the screen view to see content in greater detail. Here's an example."* We presented the 10 functions to our participants in random order. To quantify gesture differentiability with IMU and EMG sensors, we asked participants to perform their personalized gesture for the corresponding function 10 times. Participants could take as much time as they wanted to come up with their gesture, and they were given ample opportunities to take breaks. We instructed participants to use either their hand affected by their disability, both hands, or neither hand (i.e., head or shoulder movement). If both sides were affected by their disability, participants could choose which hand to use. Participants were told that the sensors attached to them could not sense eye movement but could sense muscle activation in their arms, shoulder, and neck even if they were not physically moving their body. At the end, we asked our participants how they came up with their personalized gesture set and why they chose one hand, two hands, or no hands to do the gestures.

3.4 Qualitative Analysis

To determine 1) whether our participants' gestures meet ability assumptions underlying current standardized upper-body gestures and 2) the types of sensors that could potentially sense our participants' gestures, we performed qualitative analysis on the personalized gesture set. We analyzed video recordings of the gestures that our participants performed. We coded the body part used to perform the gesture (left arm, right arm, both arms, head, shoulders), preference of lifting arms off armrest, and whether participants performed dynamic gestures where they moved a body part or static gestures where they activated their muscles but did not move their body in space.

Although developing a unified gesture set was not the goal of this work, we grouped similar gestures to characterize whether there were any trends in the types of gestures that participants designed. We chose to group gestures together based on whether the primary movement related to the function was the same. For example, for the *move* function, many participants raised their arms to chest-height and moved their arm from left to right. Participants who could move their fingers tended to point at the screen with their index finger, whereas participants who could not move their fingers pointed their whole hand at the screen. Both types of movements were coded as "move hand from left to right in mid-air", as that was the primary gesture relating to the *move* function. We also analyzed participants' interviews to understand their rationale of how they came up with the gestures and why they decided to use one versus two hands versus another part of their body.

One author finalized the code book, and another author applied the code book to 10% of the data by coding one gesture corresponding to a random function for each participant. We computed inter-rater reliability using Cohen's Kappa [10] for each item of interest, following recommendations from McDonald et al. [37]. Cohen's Kappa ranges from 0 to 1, with 0 being no agreement between raters, and 1 being complete agreement between raters. For coding similar gestures, as we had a very small number of gestures for each function, we computed the pooled Kappa to summarize the inter-rater reliability [13]. The average Kappa was 0.83, with the lowest Kappa being 0.76 and highest Kappa being 1.

3.5 Quantitative Analysis

To complement our qualitative analysis, we computed 1) gesture agreement between participants and 2) heterogeneity in muscle activation to quantify how similar or different gestures between participants were. We additionally computed 3) IMU and EMG signal differentiability within and between gestures to determine what types of sensors can be used to differentiate between personalized gestures for each participant. For 3), the goal of the analysis was to determine whether it would be possible to differentiate between personalized gestures by computing distances between and within gestures—developing an algorithm that can differentiate between personalized gestures is out-of-scope for this paper, and is an important direction for future work.

To compute 2) and 3), we extracted IMU and EMG data for each gesture that participants performed. Since our 25 participants performed 10 personalized gestures for each of the 10 functions, each IMU and EMG dataset comprised 100 gestures total.

3.5.1 Gesture Agreement Between Participants. Although we did not expect high agreement due to a diverse range of abilities of our participants, we computed gesture agreement [19, 69] to ensure we had a thorough analysis. We additionally wanted to validate the importance of supporting personalized upper-body gestures for people with upper-body motor impairments. To quantify gesture agreement, we followed analysis methods from prior work by Findlater et al. [19]. We computed gesture agreement as the count of all pairs of similar gestures:

$$A_f = \sum_{g \in G_f} \frac{\binom{|g|}{2}}{\binom{N}{2}}, \tag{1}$$

where G_f is the set of gestures g for a given function f, A_f represents agreement between participants in [0, 1], and N is the number of participants who proposed gestures for f. The notation $|g|$ indicates the number of gestures that were similar, and $\binom{x}{2}$ indicates "x choose 2". For example, *delete* and *move* both had 4 groups of gestures: *delete* had groups of size 3, 4, 5, and 6, and *move* had groups of size 3, 3, 4, and 9. We computed the corresponding agreement as:

$$A_{delete} = \frac{\binom{3}{2} + \binom{4}{2} + \binom{5}{2} + \binom{6}{2}}{\binom{25}{2}} = \frac{3 + 6 + 10 + 15}{300} = 0.11, \tag{2a}$$

$$A_{move} = \frac{\binom{3}{2} + \binom{3}{2} + \binom{4}{2} + \binom{9}{2}}{\binom{25}{2}} = \frac{3 + 3 + 6 + 36}{300} = 0.16. \tag{2b}$$

We additionally computed the percentage of participants who came up with unique gestures that no one else performed to highlight the heterogeneity in gesture designs.

3.5.2 Heterogenity in Muscle Activation. One important question that can drive future gesture recognition approaches is how variable participants gestural preferences are quantitatively—for example, are there certain muscle groups that all participants prefer to activate, or is each participant unique in their muscle activation preference? We quantified this as a measure of *heterogeneity in muscle activation.* We chose to analyze EMG data because it helps us understand which muscles are being activated and because some participants performed gestures such as only pointing their finger that can be sensed by EMG sensors but not IMU sensors. If similar muscle groups are being activated across participants, this suggests that participant abilities in activating their muscles are similar and may suggest that similar gestures may work for some subsets of participants. To quantify the heterogeneity in participants' abilities and preferences to activate different muscles to perform different gestures, we computed how each measured muscle activity contributed to the signal variability.

Raw EMG signals are highly stochastic in nature, and to determine how each measured muscle contributes to the overall variability in signals, it is important to first preprocess the data through filtering and smoothing. We followed standard methods from biomechanics [12, 74]. We first obtained the filtered EMG signal by filtering the EMG signals with a 4th-order high-pass Butterworth filter at 40 Hz, de-meaning and taking the absolute value of the EMG signal, and then filtering the EMG signal with a 4th-order low-pass Butterworth filter at 40 Hz. We then smoothed out the filtered EMG data by taking the moving average of the signal with a window of 100 ms with an overlap of 0.5. This downsampled the EMG data from 2000 Hz to 20 Hz. We then stacked all ten personalized gestures that participants performed for all ten functions to obtain a dataset $X \in R^{t \times 16}$, where t is the total number of datapoints across time for the 100 gestures (10 functions × 10 gestures per function), and 16 is the number of EMG channels we obtained. We then normalized each channel to the 95% of the maximum recorded EMG signal.

To quantify which muscle the person activated the most (i.e., determine which muscle contributed to the largest variability in the dataset), we analyzed the correlation between the data reoriented along its principal components $P \in R^{t \times 16}$ and original dataset X of the dataset after performing principal component analysis (PCA). We did this by computing the dot product between the transpose of the EMG data X and the transformed data P (i.e., $N = X^T \cdot P$, where $N \in \mathbb{R}^{16 \times 16}$). N then represents the correlation between each muscle and each principal component. We then normalized each vector in N along each principal component. Although N provides us with an idea of how much each muscle contributes to each principal component, we cannot identify from this data how much each muscle contributes to the overall variability in the dataset. Therefore, we normalized each principal component by the percent variability of the overall dataset that the principal component explained by taking the dot product of each row of the absolute value of N (which represents each principal component) with the explained variance as a vector $S \in R^{1 \times 16}$ (i.e., $C = abs(N) \cdot R$, where $C \in \mathbb{R}^{16 \times 16}$ and $abs(N)$ represents taking the absolute value of each data point in N). Lastly, to obtain one number for how each muscle contributes to the overall variance in the participants' data, we summed the rows of C to obtain $C_{sum} \in \mathbb{R}^{16 \times 1}$. We plotted C_{sum} across all muscles normalized by the largest value in C_{sum} for each participant. This meant that the muscle that contributed the most to the variance in each participants' EMG signal was equal to 1.

3.5.3 IMU and EMG Signal Differentiability. An important question impacting future gesture recognizers is whether it is possible to differentiate between personalized gestures for each participant, which we quantify as *differentiability.* We wanted to understand whether it would even be possible to differentiate between different personalized gestures given the small sample size (10 gestures per function) and heterogeneity of how the participants performed each gesture (e.g., tremoring for one gesture but not another for a given function). More specifically, we computed the average *distance* within and between gestures performed by a specific participant. Smaller distances indicated smaller spread between gestures, whereas larger distances indicated larger spread between gestures. Ideally, the distances within similar gestures would be smaller, and the distances between different gestures representing different functions would be larger. Importantly, to ensure that the gestures are differentiable, the spread of distances within gestures must be significantly smaller than the distances between gestures. Otherwise, it would be challenging to differentiate between different gestures representing different functions.

Comparing IMU and EMG signals is complicated by the fact that they sample at different rates, and with different numbers of channels (16 and 72, respectively). Before comparing them, we transformed the signals into the same vector space. We first resampled all IMU and EMG signals for each gesture to 64 time points. Next, to ensure that the different number of IMU and EMG channels does not affect the distance computed between vectors, we performed PCA on the channels for each sensor, and then selected the top 11 components as our vector space, which explained at least 80% of the variance in IMU and EMG data for each participant and each gesture. Then, for each sensor (IMU and EMG), we stacked the 11 time-varying principal components for each gesture i to obtain one vector v_i of length 704. We normalized each vector to unit length (i.e., the L_2 norm of v_i is equal to 1).

To quantify the differentiability within gestures for a given function, we computed the distance d_f between the centroid c_f of the 10 gestures performed for a single function f and the vector representing a single gesture v_i:

$$d_f = v_i - c_f, \quad c_f = \frac{\sum_i v_i}{n}, \tag{3}$$

where n is the number of gestures completed per function for each participant (10 in this case). We then computed the average distance for each participant across all functions.

To quantify the average distances between gestures representing different functions for a given participant, we computed the distance between the centroid of gestures completed for all functions c_F, and the centroid of each gesture representing a function c_f. F represents the set of all functions that the participants designed gestures for, such that $f \in F$

$$d_F = \frac{\sum_{f \in F} c_f - c_F}{|F|}, \quad c_F = \frac{\sum_F c_f}{|F|}, f \in F, \tag{4}$$

where $|F|$ represents the total number of functions.

To determine whether gestures representing different functions would be differentiable from each other with IMU and EMG sensors, we compared the differentiability within and between gestures with a paired-samples t-test with $\alpha = 0.05$. To determine whether a parameteric test was appropriate, we assessed whether our residuals were normally distributed with the Shapiro-Wilk test of residuals [54]. Both our IMU and EMG data met the normality assumption ($p = 0.893, p = 0.571$, respectively).

4 Results

Our results emphasize the importance and need for personalized upper-body gesture interfaces. First, we characterize participants' upper-body gestures as being highly personalized and ability-dependent. Second, we highlight personalized gesture properties that may impact ability assumptions underlying gesture recognition systems. Third, we demonstrate that personalized gestures representing different functions could be differentiated using either IMU and EMG sensors despite a small dataset (10 gestures per function per participant) and variability in how a given participant performed the same gesture (e.g., tremoring during some gestures but not others). To ensure clarity in our results, we reiterate that *gestures* are movements or actions that are meant to bring about a result (e.g., swipe horizontally across the screen), and *functions* are the result of a gesture or a task that the person wants to accomplish (e.g., answer a phone call).

4.1 Participants' Upper-Body Gestures are Highly Personalized and Ability-Dependent

Our participants designed a variety of personalized gestures that were specific to their abilities. Although each function had between 6-15 participants who designed the same gesture, there were at least 4 participants for each function who designed a unique gesture that no one else designed (Fig. 1). The similarity between upper-body gestures most likely arose due to participants' being inspired by prior experience of using a computer (4) or smartphone/tablet touchscreen (9) or gestures related to *"normal life [like] get out of there" (for close function)* (7). Even when participants designed the same gesture for a given function, there were often minor differences in how they performed the gesture. For example, many participants pointed at the screen for the *select* gesture. However, some participants had little to no movement in their fingers, so they pointed their entire hand at the screen, while others had good finger movement, but fatigued easily, so they pointed their finger at the screen while barely lifting their arms off the armrest. Additionally, some of our participants had involuntary movements such as spasms or tremoring when doing the gestures. This suggests that even within an accessible gesture set, there is large variability in how participants perform the gestures, and personalization may be necessary for accurate gesture recognition.

Six participants discussed that their inspiration for designing the gestures was based on *"how I would do [the gesture] with the abilities that I have"*. For example, for the *zoom-in/-out* gesture, participants who had good finger control but fatigued easily tended to pinch their thumb and index finger in and out, like using a smartphone touchscreen to minimize overall movement. However, participants who had difficulty moving their fingers tended to use two hands to move their hands closer/farther from the center of their body. Participants with more limited motion tended to come up with more creative gestures (i.e., perform gestures differently than one would do it on a touchscreen), such as moving their head towards and away from the screen for *zoom-in/-out* or flipping their arm out and in like opening and closing a book for *open/close*. Similarly, six participants discussed wanting to do gestures as easily as possible with the least amount of effort and pain. For some participants, their gestures evolved over the course of the study, where *"for the first three [gestures], when I was using my whole arm, I tried to mimic how I would do it in real life, and when I realized I have latitude for how I did the gesture, I chose to do it in the way that conserved the most energy and minimize pain upon repetition."* Another participant mentioned that they tried *"to figure out within my world, within my limitations, what [gesture] would be the easiest and take the least amount of effort."* Five participants discussed striving to make their *"movements as different as possible"*. This occasionally resulted in a gesture not tied with the meaning of the function like tilting their head to the side or shrugging a shoulder. One participant discussed how they designed gestures unrelated to prompted functions such as moving or tilting the head, neck, and shoulders because they have very limited motion.

Over 75% of participants' gestures were with one hand. Participants discussed how they used their preferred hand due to handedness (9), because one of their hands is much more impacted by their disability than the other (6), and because using one hand minimizes movement and decreases overall pain and fatigue (6). The participants who discussed doing gestures with one hand due to handedness or due to their disability affecting one side more than the other tended to use solely their left or right hand. However, some of our participants who discussed using one hand to minimize fatigue and pain switched hands back and forth or switched hands during the study. One participant stressed the importance of gesture recognition systems being able to detect gestures with both hands because *"it can help to be able to use one than the other so if one [hand] gets bad I can rely on the other...if I use both at the same time, I run through the time that my body has much faster."*

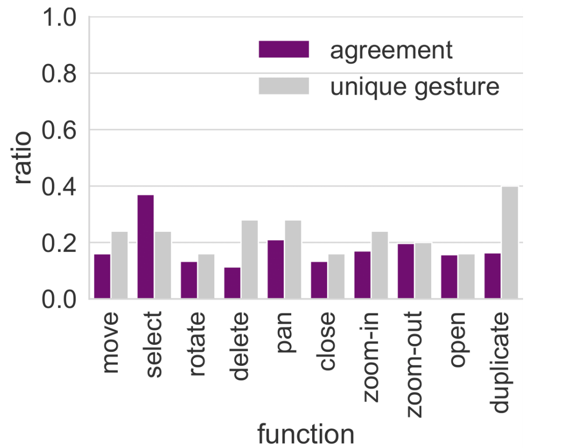

Figure 3: *Agreement and ratio of unique gestures for each tested function.* The dark purple represents agreement between different people's gestures, as computed by (1). A higher ratio closer to 1 indicates that many participants came up with similar gestures, and a lower ratio closer to 0 indicates that few participants came up with similar gestures. The light grey represents the ratio of gestures that were unique to the participant, and were not repeated by any other participants. The functions are ordered from least conceptual complexity (left) to most conceptual complexity (right) according to Wobbrock et al. [69].

4.1.1 Gesture Agreement Between Participants.

Although the goal of this paper was not to come up with a unified gesture set, we were still interested in quantifying gesture agreement between participants to highlight the heterogeneity of our participants' abilities and gesture preferences [19, 69]. The gesture agreement score [19, 65] is a score that ranges from 0 to 1, with 0 being that there was no gesture agreement between participants, and 1 being that there was perfect agreement between participants. Aside from *select*, which had a gesture agreement of 0.37, all other agreement scores ranged from 0.11 to 0.21. This suggests that coming up with a unified gesture set for users with upper-body motor impairments would be challenging and most likely not meet the abilities of all our participants.

At least four participants came up with a unique gesture that no one else did for each function we tested. The fraction of unique gestures ranged from 0.16 for *open, close* and *rotate*, to 0.4 for *duplicate* (Fig. 3). Therefore, there were no functions that had a universal accessible gesture. Some were because the participant had very limited motion, so they designed gestures that were accessible to them that weren't necessarily related to the interaction they were performing, such as shrugging one or both shoulders or squeezing their left and right fist in succession. Such participants mentioned that because their disability made it challenging to perform movements that reflected the desired function, they tried to pick random gestures that were as different as possible, even if it was not an intuitive gesture for the prompted function.

4.1.2 Muscle Activations are Heterogenous.

EMG characterization of the muscles that were activated when participants performed their personalized gestures also highlighted the heterogeneity between participants' abilities. The muscle activation of the EMG data visualizes the variability of the muscles used to perform the gestures among our participants (Fig. 4). In the figure, the x-axis corresponds to muscle group (from shoulder down to finger muscles) and the y-axis shows each participant sorted by disability type (grouped from top to bottom as spinal cord injury (`SCI`), muscular dystrophy (`MD`), peripheral neuropathy (`PN`), essential tremor (`ET`), and other. For example, participant `SCI 1` in the top row of the table had the largest muscle activation with the shoulder's right deltoid (`R_delt`) muscle and very little muscle activation with the forearm and finger muscles, suggesting that they primarily moved their arm about their right shoulder and had little movement in the rest of their arm to perform the gestures. However, participant SCI 4 (fourth from the top) had high muscle activation with their forearm's right extensor (`R_ext`) and flexor (`R_flex`) muscles, suggesting that they moved their hand about their wrist to perform gestures. There are no obvious trends as to specific muscles groups that were activated by participants with the same disability, emphasizing the heterogeneity of abilities among our participants.

4.2 Gesture Properties that Impact Ability Assumptions

We summarize various qualitative gesture properties for the 250 gestures that participants performed (10 prompted interactions per person × 25 participants), including body part used, preference of lifting arms off the armrest, dynamic gesture preferences, and gesture similarity. Our results suggest that: 1) it is important to sense movement in the whole upper-body instead of just the hands and arms, 2) algorithms that assume that a gesture is performed in mid-air may not perform well for users who experience fatigue, and 3) sensors that require movement to classify gestures may not perform well for participants who performed gestures by flexing their muscles but not visibly moving.

4.2.1 Preference on Body Part Used.

Out of 250 gestures, 131 (52%) were with the right hand, 61 (24%) were with the left hand, 38 (15%) were with both hands, 12 (5%) were with the head/neck, and 8 (3%) were with the shoulders. All except one participant (who indicated that they were right-handed but used their left hand

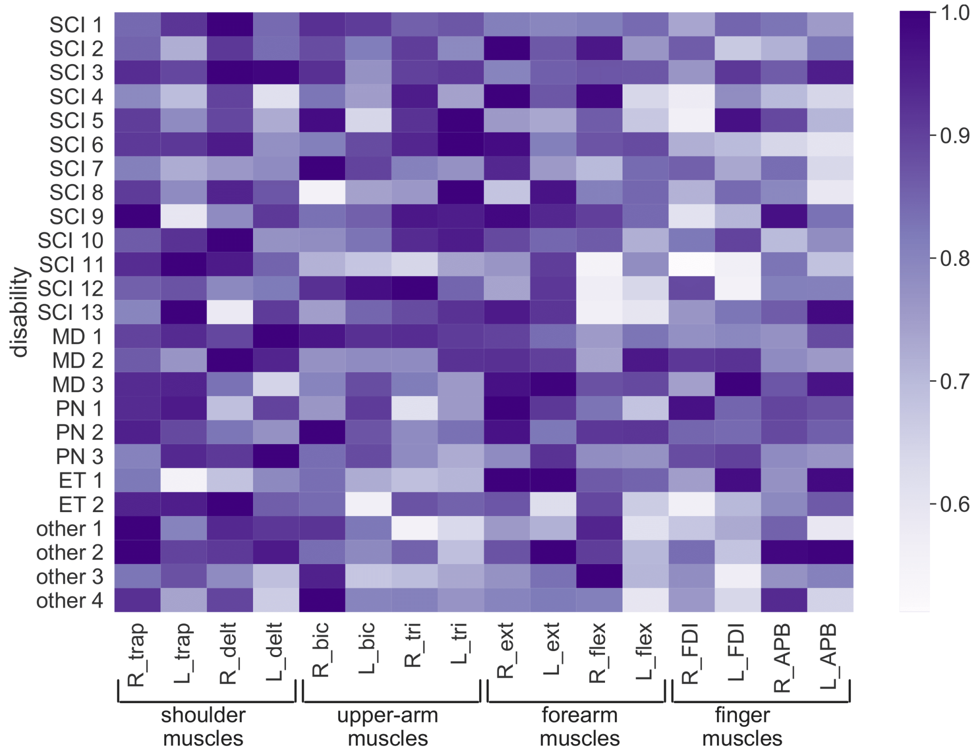

Figure 4: *Heterogeneity of Activated Muscles.* Muscle groups that the participant activated the most (i.e., muscles that contributed to the largest variability when performing gestures) are shown in dark purple, whereas muscle groups that the participant activated the least (i.e., muscles that did not contribute to variability when performing gestures) are shown in light purple and white.
`SCI` = spinal cord injury; `MD` = muscular dystrophy; `PN` = peripheral neuropathy; `ET` = essential tremor.
`R, L` indicates the right and left sides, respectively.
`trap` = trapezius muscles; `delt` = deltoid muscles; `bic` = bicep muscles; `tri` = tricep muscles; `ext` = extensor bundle; `flex` = flexor bundle; `FDI` = first dorsal interosseous; `APB` = abductor pollicis brevis.

for all gestures) used their preferred hand or had an even mix of using different body parts. Participants with greater disability (i.e., discussed having limited function in one or both arms) tended to use their head/neck and shoulders rather than using their hands and arms. None of the participants performed gestures that could not be captured by the EMG sensors, as the sensor placed on the trapezius can sense when the participant moves their head and neck, and sensors were directly placed on the rest of the arm. However, a sensor that is solely on the user's wrist would not be able to sense the 8% of gestures that participants performed with their head, neck, or shoulders.

4.2.2 Preference on Lifting Arm off Armrest. 120 (48%) gestures were with participants' arms off their armrest, 77 (30%) gestures were with participants' arms on the armrest, and in 53 (21%) gestures, participants barely moved their arms off the armrest. Of the 25 participants, 9 participants lifted their arms off their armrest for all gestures, 9 participants didn't lift their arms off their armrest for any of the gestures, 2 participants barely lifted their arms off their armrest, and 5 participants were gesture-dependent. Some participants initially started with their arms in mid-air like using a touchscreen, and then they realized that they could minimize effort and decrease fatigue by performing gestures with just their fingers, while resting their hand on their armrest. This has implications for standard gesture sets—currently, many of the standardized upper-body gesture sets that are available for gesture recognition for smart homes [58], wall-displays [64] or augmented or virtual reality [39, 40, 71] assume that the user is performing the gesture in mid-air. Since we had many participants who did not raise their arms to chest-level to perform gestures, this may not be a good assumption for users with upper-body motor impairments and cause gesture accuracy to decrease for such individuals. Their gestures would not be consistent with where the algorithm expects the hand/arm to be relative to the rest of the user's body.

4.2.3 Dynamic Gesture Preferences. Almost all gestures (226 or 90%) were dynamic gestures where participants moved their head, shoulders, arms, hands, or fingers. However, 24 gestures (10%) were gestures where people activated their muscles, but did not visibly move. The three participants who did the majority of the gestures that involved flexing their muscles discussed experiencing significant weakness and difficulty moving their limbs. This has implications for the type of sensors that can be used to identify what kinds of gestures people are performing. Sensors that require movement to identify which gesture was performed (e.g., cameras, IMU sensors) may not work for those participants. For participants who experience significant muscle weakness, using a sensor like EMG sensors that can sense muscle activation without movement may be a necessity for accessibility, rather than a preference.

4.3 IMU and EMG Sensors Can Differentiate Between Personalized Gestures

To quantitatively characterize whether it would be possible to differentiate between personalized gestures for each participant, we compared the distances within gestures for a given function (e.g., comparing distances between gestures performed for *zoom-in* for one participant) and distances between different gestures (e.g., distance between a gesture performed for *zoom-in* and *select* for one participant). We wanted to understand whether it would even be possible to differentiate between different personalized gestures given the small sample size (10 gestures per function) and heterogeneity of how the participants performed each gesture (e.g., tremoring for one gesture but not another). We analyzed this by comparing the average distance from the centroid of gestures performed by each participant (i.e., *within gestures*), and the average distance from the centroid of each gesture performed for a given function (i.e., *between gestures*). Ideally, the *within gestures* distance will be small so that if the person performs the same gesture, it can be identified as the same function, and the *between gestures* distance will be large so that different gestures can be identified as different functions.

For both IMU and EMG sensors, the within-gestures distance was significantly smaller than the between-gestures distance (Fig. 5; IMU: $t(24) = -4.66, p < 0.0001$; EMG: $t(24) = -7.85, p < 0.0001$). The average distance within gestures was 0.49 ± 0.16 (mean ± standard deviation) and 0.45 ± 0.11 for the IMU and EMG sensors, respectively. The average distance between gestures was 0.73 ± 0.09 with IMU sensors and 0.66 ± 0.07 with EMG sensors. Our preliminary characterization suggests that it would be possible to identify different personalized gestures for different functions with IMU or EMG sensors distributed across the upper-body and that there are clusters of gestures representing the same function for each participant.

5 Discussion

Our quantitative and qualitative study results emphasize the wide heterogeneity in upper-body gesture abilities of users with upper-body motor impairments. Even participants with the same self-reported disability used very different muscle groups to perform their gestures, and participants used their whole upper-body, including their arms, shoulders, neck, and head. We present three considerations when designing accessible upper-body gesture interfaces and highlight limitations and opportunities for future work.

5.1 Considerations for Sensor and Algorithm Choice for Upper-Body Gesture Recognition

Our qualitative and quantitative characterization of the personalized gesture sets that participants produced highlights important considerations when designing sensors and algorithms for ability-inclusive upper-body gesture recognition. Below, we summarize

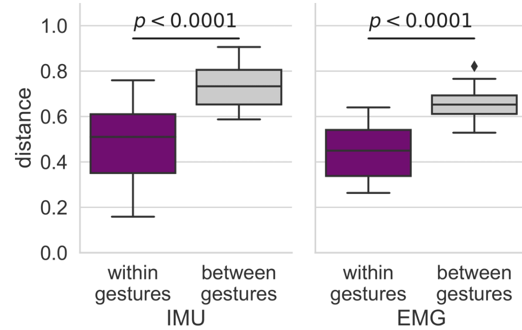

Figure 5: *Distances within and between gestures.* Distributions (median, inter-quartile range) of distance within (dark purple) and between (light grey) gestures for 25 participants with upper-body motor impairments. Within gestures distance indicates the distance within personalized gestures performed for a given function for a specific participant. Between gestures distance indicates the distance between personalized gestures performed for all tested functions for a specific participant. Ideally, within gestures distances should be small and between gestures distances should be large to differentiate between personalized gestures designed for different functions.

three considerations to make for sensor choice and algorithm development when developing ability-inclusive upper-body gesture recognition systems.

5.1.1 Consideration 1: Track the Whole Upper-Body. To ensure ability inclusivity and accessibility of upper-body gestures, it is important that the sensing mechanism can sense movements from the whole upper-body, including the head, neck, shoulders, and both arms. Solely measuring gestures from one or both arms provides insufficient coverage for the types of personalized gestures that users with upper-body motor impairments may perform. Additionally, in line with prior recommendations from Carreira et al. [6], it is important to sense gestures from both arms, rather than solely from one arm so that users who fatigue easily can switch hands during single-handed gestures. This consideration for combating fatigue by switching hands also has implications for algorithm design —for users who experience fatigue, it is important to ensure that personalized gestures can be classified regardless of whether the person is using their left or right hand. Sensors that are solely placed on the wrist of one hand, like a smartwatch, may not provide sufficient coverage to detect gestures using parts of the body other than the arm or gestures using the other arm.

5.1.2 Consideration 2: Use Sensing Mechanisms that are Agnostic to the Location and Orientation of the Body. For participant gestures that were performed with the person's hands and arms, our results highlight the heterogeneity in the location of the person's arm relative to the rest of the body when the person performs the gesture. Some of our participants performed their hand gestures in mid-air at chest-level, while others performed their gestures with their hands at hip-level or while resting their hands on their laps or on an armrest. Such gestures may be challenging to classify if the gesture recognizer depends on the hand being at a specific location relative to the rest of the body, such as in mid-air at chest-level. A gesture recognition algorithm that takes in features that are not related to the location of the hand relative to the rest of the body (e.g., joint angles from a depth camera) or using a sensor whose features are solely dependent on the movement of that sensor (e.g., IMU or EMG sensor on the wrist) may improve classification accuracy for ability-diverse gestures.

5.1.3 Consideration 3: Use Sensors That Can Sense Muscle Activations without Movement.

While most of our participants performed dynamic gestures where they moved their arm, our participants activated their muscles but did not move in 10% of the gestures. Gesture classifiers that require dynamic movement, such as ones that use depth cameras to estimate changes in pose over time, may not be able to sense such gestures. To ensure that such gestures can be captured and classified, sensors like EMG sensors that can sense muscle activations regardless of whether the user moved or not is an important aspect of an accessible gesture classifier. Alternatively, in situations where it is not possible to incorporate sensors that can track muscle activations, it may be important to incorporate sensors that can track eye or facial movement [16, 75].

5.2 Adding Isotonic and Isometric Dynamic Gestures to Gesture Taxonomy

Although performing a formal analysis on gesture taxonomy was outside the scope of this current work, we highlight and recommend a key addition to the original gesture taxonomy introduced in Wobbrock et al. [69]. For user-defined gestures, one of the ways in which gestures can be categorized is by the form, and whether it is a dynamic gesture or a static gesture. Dynamic gestures involve hand or arm movement over time, whereas static gestures do not vary over time [61]. During our study, we found that several of our participants performed gestures that did not appear to fit into either category, where they activated their muscles but did not move their arms. To us, this seemed different from a static gesture, where there is no change over time in the person's body position. Therefore, taking terminology from biomechanics, we recommend introducing the terms *isotonic* and *isometric* gestures as subcategories of dynamic gestures [46]. We define *isotonic gestures* as ones where the person's hand or arm pose changes over time, and *isometric gestures* as ones where the person's pose does not change, but their muscles flex and activate over time.

5.3 Sensor Fusion to Optimize Upper-Body Gesture Accessibility

Our quantitative analysis comparing IMU and EMG sensor differentiability between and within gestures demonstrated that both IMU and EMG sensors can differentiate between gestures designed for different functions. Although IMU sensors are currently more widely available, we found that there were some participant gestures where it would be challenging or impossible for motion-based sensors like IMU sensors to differentiate, such as when a gesture is an isometric gesture (i.e., the person activates their muscles, but does not move).

One thing to note is that our sensor placements are unrealistic for real-world applications, as IMU and EMG sensors were placed precisely on the muscles of interest. This was a deliberate choice that we made, as we wanted to determine whether it would be possible to differentiate between personalized gestures in an ideal scenario with high-fidelity sensors. Sensors that are placed on one part of the body, like wristband IMU and EMG sensors [2] are much more realistic for real-world applications. However, this is directly in conflict with our **Consideration 1: Track the Whole Upper-Body**. In such scenarios, sensor fusion, where multiple sensor types are used for gesture classification, could provide the most optimal classification [28]. For example, IMU or EMG sensors placed on the wrist could differentiate between small hand or finger gestures or isometric gestures, while camera-based sensors could differentiate between larger gestures involving the head or neck. However, too many sensors could make it challenging to process the data and result in multiple correlated data streams. New filtering and data-dropping methods are needed to ensure optimal classification performance.

5.4 Personalized Upper-Body Gestures for All Users

Although this paper focused on personalized upper-body gestures for people with upper-body motor impairments, personalized gestures may benefit users without disabilities as well. Prior work from Wu et al. [72] demonstrated that gesture agreement is low (below 0.36) for participants without disabilities designing mid-air gestures, and the types of gestures participants think of may depend on cultural context. Wu et al. [72] discussed how the low gesture agreement may be because participants are unaccustomed to using mid-air gesture interfaces. However, gesture agreement was fairly high (between 0.2 and 1.0) in Wobbrock et al. [69] despite participants being unaccustomed to tabletop touchscreen interfaces at the time. This suggests that the low agreement could also be due to the increased degrees-of-freedom afforded by a mid-air interface compared to a touchscreen interface.

Additionally, prior work on mid-air gestures with older adults demonstrated the importance of personalizing standardized gesture sets to the preferences of the individual (e.g., gesture amplitude and speed) [6, 18]. Similarly, prior work on eyelid gestures also recommended personalizing gestures as a next step [16]. Fully personalized gestures may further enhance gesture accessibility for users with and without motor impairments.

Despite the low gesture agreement in our study, many of our participants mentioned that their gestures were inspired by the way they or others currently interact with computers and smartphones. This suggests that there was some legacy bias in participants' chosen gestures. Indeed, some of our participants discussed how their initial gestures mimicked touchscreen gestures, whereas their later gestures were more personalized to their abilities. Future work should consider how to prompt participants to consider personalized gestures beyond those that are currently used for computers and smartphones.

Lastly, since personalized gesture sets are easier for users to recall than pre-designed gesture sets [45], personalized gesture interfaces may improve usability for users without disabilities as well, and is a consideration that should be made in future work involving mid-air gesture design.

5.5 Limitations

There are several limitations associated with our work and opportunities for future work. First, prior work has demonstrated that cultural context may influence the types of gestures that participants come up with [72], highlighting the importance of including participants from diverse backgrounds. Our study participants were limited to participants who lived within driving distance to our study site and could arrange for transportation and caregiving needs. We attempted to alleviate such barriers by providing reimbursement for transportation and a $50 / hour compensation for their time spent doing the study. Although we successfully recruited participants with representative genders and ages, we did experience difficulty in recruiting participants who did not identify as Caucasian/White. Having many participants from potentially similar cultural backgrounds (e.g., participants who are Caucasian/White and live within driving distance to the testing site) may have affected the types of gestures that participants came up with [72].

We additionally solely investigated upper-body gestures, and participants were told that the sensors could not detect eye or facial movement. Several of our participants mentioned that they would be interested in incorporating eye or facial gestures as part of their personalized gesture set. Future work could consider how the results of our work, Zhao et al. [75], and Fan et al. [16] could be combined to further enhance gesture accessibility.

Another limitation of our study was that we solely compared gesture differentiability between IMU and EMG sensors, and we did not compare gesture differentiability with camera-based sensors that extract poses with computer vision. This was due to our interest in quantifying differentiability of signals measured from wearable sensors, as wearable sensors could enable always-on continuous gesture input. An interesting consideration for future work is how distance from camera-based sensors affect the quality of pose extraction, as some of our participants sat further away from the experimental desk because their wheelchairs did not fit under the desk. Lastly, almost half our participants had spinal cord injury and implies that the personalized gestures we analyzed in this study may be more applicable to this group. Further work should investigate participants with other types of upper-body motor impairments that may result in different movements.

6 Conclusion

Our work demonstrates the importance of designing personalized gestures that fit the diverse abilities of users with upper-body motor impairments. We highlight three considerations—1) track the whole upper-body, 2) use sensing mechanisms that are agnostic to the location and orientation of the body, and 3) use sensors that can sense muscle activations without movement—when designing inclusive upper-body gesture recognition systems. Both IMU and EMG sensors are suitable for differentiating between personalized gestures designed for different functions, and fusing signals from different modalities depending on the person's abilities is an important area of future work.

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References

[1] Bashar Altakrouri, Daniel Burmeister, Dennis Boldt, and Andreas Schrader. 2016. Insights on the impact of physical impairments in full-body motion gesture elicitation studies. In *Proceedings of the 9th Nordic Conference on Human-Computer Interaction*. 1–10.

[2] Apple. 2022. Use AssistiveTouch on your Apple Watch. https://support.apple.com/en-us/HT212760 [Accessed: April 27, 2023].

[3] Jan Bobeth, Susanne Schmehl, Ernst Kruijff, Stephanie Deutsch, and Manfred Tscheligi. 2012. Evaluating performance and acceptance of older adults using freehand gestures for TV menu control. In *Proceedings of the 10th European conference on Interactive tv and video*. 35–44.

[4] Massimo Camplani and Luis Salgado. 2014. Background foreground segmentation with RGB-D Kinect data: An efficient combination of classifiers. *Journal of Visual Communication and Image Representation* 25, 1 (2014), 122–136.

[5] Fabio M Caputo, Pietro Prebianca, Alessandro Carcangiu, Lucio D Spano, and Andrea Giachetti. 2018. Comparing 3D trajectories for simple mid-air gesture recognition. *Computers & Graphics* 73 (2018), 17–25.

[6] Micael Carreira, Karine Lan Hing Ting, Petra Csobanka, and Daniel Gonçalves. 2017. Evaluation of in-air hand gestures interaction for older people. *Universal Access in the Information Society* 16 (2017), 561–580.

[7] Patrick Carrington, Jian-Ming Chang, Kevin Chang, Catherine Hornback, Amy Hurst, and Shaun K Kane. 2016. The gest-rest family: Exploring input possibilities for wheelchair armrests. *ACM Transactions on Accessible Computing (TACCESS)* 8, 3 (2016), 1–24.

[8] Patrick Carrington, Amy Hurst, and Shaun K Kane. 2014. Wearables and chairables: inclusive design of mobile input and output techniques for power wheelchair users. In *Proceedings of the SIGCHI Conference on human factors in computing systems*. 3103–3112.

[9] Ross A Clark, Benjamin F Mentiplay, Emma Hough, and Yong Hao Pua. 2019. Three-dimensional cameras and skeleton pose tracking for physical function assessment: A review of uses, validity, current developments and Kinect alternatives. *Gait & posture* 68 (2019), 193–200.

[10] Jacob Cohen. 1960. A coefficient of agreement for nominal scales. *Educational and psychological measurement* 20, 1 (1960), 37–46.

[11] Eleanor Criswell. 2010. *Cram's introduction to surface electromyography*. Jones & Bartlett Publishers.

[12] Carlo J De Luca. 1997. The use of surface electromyography in biomechanics. *Journal of applied biomechanics* 13, 2 (1997), 135–163.

[13] Han De Vries, Marc N Elliott, David E Kanouse, and Stephanie S Teleki. 2008. Using pooled kappa to summarize interrater agreement across many items. *Field methods* 20, 3 (2008), 272–282.

[14] Nem Khan Dim and Xiangshi Ren. 2014. Designing motion gesture interfaces in mobile phones for blind people. *Journal of Computer Science and technology* 29, 5 (2014), 812–824.

[15] Tim Duente, Justin Schulte, Max Pfeiffer, and Michael Rohs. 2018. Muscleio: Muscle-based input and output for casual notifications. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 2 (2018), 1–21.

[16] Mingming Fan, Zhen Li, and Franklin Mingzhe Li. 2020. Eyelid gestures on mobile devices for people with motor impairments. In *Proceedings of the 22nd International ACM SIGACCESS Conference on Computers and Accessibility*. 1–8.

[17] Michela Ferron, Nadia Mana, and Ornella Mich. 2019. Designing mid-air gesture interaction with mobile devices for older adults. *Perspectives on human-computer interaction research with older people* (2019), 81–100.

[18] Michela Ferron, Nadia Mana, Ornella Mich, and Christopher Reeves. 2018. Design of multimodal interaction with mobile devices. Challenges for visually impaired and elderly users. In *Proceedings of the 3rd International Conference on Human Computer Interaction Theory and Applications (HUCAPP)*. 140–146.

[19] Leah Findlater, Ben Lee, and Jacob Wobbrock. 2012. Beyond QWERTY: augmenting touch screen keyboards with multi-touch gestures for non-alphanumeric input. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2679–2682.

[20] Leah Findlater and Jacob Wobbrock. 2012. Personalized input: improving ten-finger touchscreen typing through automatic adaptation. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 815–824.

[21] Leah Findlater, Jacob O Wobbrock, and Daniel Wigdor. 2011. Typing on flat glass: examining ten-finger expert typing patterns on touch surfaces. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 2453–2462.

[22] Krzysztof Z Gajos, Amy Hurst, and Leah Findlater. 2012. Personalized dynamic accessibility. *Interactions* 19, 2 (2012), 69–73.

[23] Krzysztof Z Gajos, Jacob O Wobbrock, and Daniel S Weld. 2008. Improving the performance of motor-impaired users with automatically-generated, ability-based interfaces. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*. 1257–1266.

[24] Kathrin Gerling, Ian Livingston, Lennart Nacke, and Regan Mandryk. 2012. Full-body motion-based game interaction for older adults. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1873–1882.

[25] Kathrin M Gerling, Kristen K Dergousoff, Regan L Mandryk, et al. 2013. Is movement better? Comparing sedentary and motion-based game controls for older adults. In *Proceedings-Graphics Interface*. Canadian Information Processing Society, 133–140.

[26] Seniam group. 2000. Recommendations for sensor locations on individual muscles. http://www.seniam.org/ [Accessed: April 13, 2023].

[27] Donny Huang, Xiaoyi Zhang, T Scott Saponas, James Fogarty, and Shyamnath Gollakota. 2015. Leveraging dual-observable input for fine-grained thumb interaction using forearm EMG. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*. 523–528.

[28] Yangjian Huang, Weichao Guo, Jianwei Liu, Jiayuan He, Haisheng Xia, Xinjun Sheng, Haitao Wang, Xuetao Feng, and Peter B Shull. 2015. Preliminary testing of a hand gesture recognition wristband based on emg and inertial sensor fusion. In *Intelligent Robotics and Applications: 8th International Conference, ICIRA 2015, Portsmouth, UK, August 24-27, 2015, Proceedings, Part I 8*. Springer, 359–367.

[29] Shaun K Kane, Jacob O Wobbrock, and Richard E Ladner. 2011. Usable gestures for blind people: understanding preference and performance. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 413–422.

[30] BC Kennedy, Solway S CA BDE, and S McConnell. 2011. Disabilities of the arm, shoulder and hand (DASH). The DASH and QuickDASH outcome measure User's manual. Toronto: Ontario Inst. *Work Heal* (2011).

[31] Christine Kühnel, Tilo Westermann, Fabian Hemmert, Sven Kratz, Alexander Müller, and Sebastian Möller. 2011. I'm home: Defining and evaluating a gesture set for smart-home control. *International Journal of Human-Computer Studies* 69, 11 (2011), 693–704.

[32] Seong Kyu Leem, Faheem Khan, and Sung Ho Cho. 2019. Detecting mid-air gestures for digit writing with radio sensors and a CNN. *IEEE Transactions on Instrumentation and Measurement* 69, 4 (2019), 1066–1081.

[33] Qi Feng Liu, Keiko Katsuragawa, and Edward Lank. 2019. Eliciting Wrist and Finger Gestures to Guide Recognizer Design.. In *Graphics Interface*. 9–1.

[34] Kelly Mack, Emma J McDonnell, Leah Findlater, and Heather D Evans. 2022. Chronically Under-Addressed: Considerations for HCI Accessibility Practice with Chronically Ill People. In *Proceedings of the 24th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–15.

[35] Meethu Malu, Pramod Chundury, and Leah Findlater. 2018. Exploring accessible smartwatch interactions for people with upper body motor impairments. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–12.

[36] Meethu Malu and Leah Findlater. 2015. Personalized, wearable control of a head-mounted display for users with upper body motor impairments. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 221–230.

[37] Nora McDonald, Sarita Schoenebeck, and Andrea Forte. 2019. Reliability and inter-rater reliability in qualitative research: Norms and guidelines for CSCW and HCI practice. *Proceedings of the ACM on human-computer interaction* 3, CSCW (2019), 1–23.

[38] Arc Media. 2016. Thalmic Labs – Myo Retail Launch. https://www.youtube.com/watch?v=A8lGstYAY14&ab_channel=ArcMedia [Accessed: April 12, 2023].

[39] Meta. 2023. Getting started with Hand Tracking on Meta Quest headsets. https://www.meta.com/help/quest/articles/headsets-and-accessories/controllers-and-hand-tracking/hand-tracking-quest-2/ [Accessed: April 10, 2023].

[40] Microsoft. 2021. HoloLens 2 gestures for authoring and navigating in Dynamics 365 Guides. https://learn.microsoft.com/en-us/dynamics365/mixed-reality/guides/authoring-gestures-hl2 [Accessed: April 10, 2023].

[41] Microsoft. 2023. Azure Kinect DK. https://www.microsoft.com/en-us/d/azure-kinect-dk/8pp5vxmd9nhq?activetab=pivot:overviewtab [Accessed: April 12, 2023].

[42] Meredith Ringel Morris. 2012. Web on the wall: insights from a multimodal interaction elicitation study. In *Proceedings of the 2012 ACM international conference on Interactive tabletops and surfaces*. 95–104.

[43] Meredith Ringel Morris, Jacob O Wobbrock, and Andrew D Wilson. 2010. Understanding users' preferences for surface gestures. In *Proceedings of graphics interface 2010*. 261–268.

[44] Martez E Mott, Radu-Daniel Vatavu, Shaun K Kane, and Jacob O Wobbrock. 2016. Smart touch: Improving touch accuracy for people with motor impairments with template matching. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. 1934–1946.

[45] Miguel A Nacenta, Yemliha Kamber, Yizhou Qiang, and Per Ola Kristensson. 2013. Memorability of pre-designed and user-defined gesture sets. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1099–1108.

[46] Nurhazimah Nazmi, Mohd Azizi Abdul Rahman, Shin-Ichiroh Yamamoto, Siti Anom Ahmad, Hairi Zamzuri, and Saiful Amri Mazlan. 2016. A review of classification techniques of EMG signals during isotonic and isometric contractions. *Sensors* 16, 8 (2016), 1304.

[47] Sameera Palipana, Dariush Salami, Luis A Leiva, and Stephan Sigg. 2021. Pantomime: Mid-air gesture recognition with sparse millimeter-wave radar point clouds. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 5, 1 (2021), 1–27.

[48] Thammathip Piumsomboon, Adrian Clark, Mark Billinghurst, and Andy Cockburn. 2013. User-defined gestures for augmented reality. In *CHI'13 Extended Abstracts on Human Factors in Computing Systems*. 955–960.

[49] Daniel Roetenberg, Henk Luinge, Per Slycke, et al. 2009. Xsens MVN: Full 6DOF human motion tracking using miniature inertial sensors. *Xsens Motion Technologies BV, Tech. Rep* 1 (2009), 1–7.

[50] Simon Ruffieux, Denis Lalanne, and Elena Mugellini. 2013. ChAirGest: a challenge for multimodal mid-air gesture recognition for close HCI. In *Proceedings of the 15th ACM on International conference on multimodal interaction*. 483–488.

[51] Jaime Ruiz, Yang Li, and Edward Lank. 2011. User-defined motion gestures for mobile interaction. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 197–206.

[52] T Scott Saponas, Desney S Tan, Dan Morris, Ravin Balakrishnan, Jim Turner, and James A Landay. 2009. Enabling always-available input with muscle-computer interfaces. In *Proceedings of the 22nd annual ACM symposium on User interface software and technology*. 167–176.

[53] Ovidiu-Andrei Schipor, Laura-Bianca Bilius, and Radu-Daniel Vatavu. 2022. WearSkill: personalized and interchangeable input with wearables for users with motor impairments. In *Proceedings of the 19th International Web for All Conference*. 1–5.

[54] Samuel Sanford Shapiro and Martin B Wilk. 1965. An analysis of variance test for normality (complete samples). *Biometrika* 52, 3/4 (1965), 591–611.

[55] Benjamin R Shuman, Marije Goudriaan, Kaat Desloovere, Michael H Schwartz, and Katherine M Steele. 2019. Muscle synergies demonstrate only minimal changes after treatment in cerebral palsy. *Journal of neuroengineering and rehabilitation* 16 (2019), 1–10.

[56] Alexandru-Ionut Siean and Radu-Daniel Vatavu. 2021. Wearable interactions for users with motor impairments: systematic review, inventory, and research implications. In *Proceedings of the 23rd International ACM SIGACCESS Conference on Computers and Accessibility*. 1–15.

[57] Jean Vanderdonckt, Nathan Magrofuoco, Suzanne Kieffer, Jorge Pérez, Ysabelle Rase, Paolo Roselli, and Santiago Villarreal. 2019. Head and shoulders gestures: Exploring user-defined gestures with upper body. In *Design, User Experience, and Usability. User Experience in Advanced Technological Environments: 8th International Conference, DUXU 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings, Part II 21*. Springer, 192–213.

[58] Radu-Daniel Vatavu. 2012. User-defined gestures for free-hand TV control. In *Proceedings of the 10th European conference on Interactive tv and video*. 45–48.

[59] Radu-Daniel Vatavu and Ovidiu-Ciprian Ungurean. 2022. Understanding Gesture Input Articulation with Upper-Body Wearables for Users with Upper-Body Motor Impairments. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–16.

[60] Santiago Villarreal-Narvaez, Jean Vanderdonckt, Radu-Daniel Vatavu, and Jacob O Wobbrock. 2020. A systematic review of gesture elicitation studies: What can we learn from 216 studies?. In *Proceedings of the 2020 ACM designing interactive systems conference*. 855–872.

[61] Panagiotis Vogiatzidakis and Panayiotis Koutsabasis. 2018. Gesture elicitation studies for mid-air interaction: A review. *Multimodal Technologies and Interaction* 2, 4 (2018), 65.

[62] Tijana Vuletic, Alex Duffy, Laura Hay, Chris McTeague, Gerard Campbell, and Madeleine Grealy. 2019. Systematic literature review of hand gestures used in human computer interaction interfaces. *International Journal of Human-Computer Studies* 129 (2019), 74–94.

[63] Tianyi Wang, Xun Qian, Fengming He, Xiyun Hu, Yuanzhi Cao, and Karthik Ramani. 2021. GesturAR: An authoring system for creating freehand interactive augmented reality applications. In *The 34th Annual ACM Symposium on User Interface Software and Technology*. 552–567.

[64] Markus L Wittorf and Mikkel R Jakobsen. 2016. Eliciting mid-air gestures for wall-display interaction. In *Proceedings of the 9th Nordic Conference on Human-Computer Interaction*. 1–4.

[65] Jacob O Wobbrock, Htet Htet Aung, Brandon Rothrock, and Brad A Myers. 2005. Maximizing the guessability of symbolic input. In *CHI'05 extended abstracts on Human Factors in Computing Systems*. 1869–1872.

[66] Jacob O Wobbrock, James Fogarty, Shih-Yen Liu, Shunichi Kimuro, and Susumu Harada. 2009. The angle mouse: target-agnostic dynamic gain adjustment based on angular deviation. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 1401–1410.

[67] Jacob O Wobbrock, Krzysztof Z Gajos, Shaun K Kane, and Gregg C Vanderheiden. 2018. Ability-based design. *Commun. ACM* 61, 6 (2018), 62–71.

[68] Jacob O Wobbrock, Shaun K Kane, Krzysztof Z Gajos, Susumu Harada, and Jon Froehlich. 2011. Ability-based design: Concept, principles and examples. *ACM Transactions on Accessible Computing (TACCESS)* 3, 3 (2011), 1–27.

[69] Jacob O Wobbrock, Meredith Ringel Morris, and Andrew D Wilson. 2009. User-defined gestures for surface computing. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1083–1092.

[70] Jacob O Wobbrock, Andrew D Wilson, and Yang Li. 2007. Gestures without libraries, toolkits or training: a $1 recognizer for user interface prototypes. In *Proceedings of the 20th annual ACM symposium on User interface software and technology*. 159–168.

[71] Huiyue Wu, Yu Wang, Jiali Qiu, Jiayi Liu, and Xiaolong Zhang. 2019. User-defined gesture interaction for immersive VR shopping applications. *Behaviour & Information Technology* 38, 7 (2019), 726–741.

[72] Huiyue Wu, Shaoke Zhang, Jiayi Liu, Jiali Qiu, and Xiaolong Zhang. 2019. The gesture disagreement problem in free-hand gesture interaction. *International Journal of Human–Computer Interaction* 35, 12 (2019), 1102–1114.

[73] Xuhai Xu, Jun Gong, Carolina Brum, Lilian Liang, Bongsoo Suh, Shivam Kumar Gupta, Yash Agarwal, Laurence Lindsey, Runchang Kang, Behrooz Shahsavari, et al. 2022. Enabling hand gesture customization on wrist-worn devices. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–19.

[74] Momona Yamagami, Keshia M Peters, Ivana Milovanovic, Irene Kuang, Zeyu Yang, Nanshu Lu, and Katherine M Steele. 2018. Assessment of dry epidermal electrodes for long-term electromyography measurements. *Sensors* 18, 4 (2018), 1269.

[75] Xuan Zhao, Mingming Fan, and Teng Han. 2022. "I Don't Want People to Look At Me Differently" Designing User-Defined Above-the-Neck Gestures for People with Upper Body Motor Impairments. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–15.

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